Environmental facilitators and barriers to student persistence in online courses: reliability and validity of new scales

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Abstract

This study aimed at building a reliable and valid scale for environmental factors related to student persistence in online courses, particularly relevant for adults or lifelong learners. Drawing on Kember and colleagues (1994)' social integration and external attribution scales and subscales as a starting point, data collected in Canadian universities were randomly split into two samples. The first sample ($n_1 = 385$) was used to explore the data set through principal component and reliability analyses. These confirmed a two-factor environmental scale composed of encouragements (factor 1) and time-events items (factor 2), as well as a two-factor persistence scale that included potential dropout (factor 3) and cost-benefit items (factor 4). All factors showed a very good internal consistency. The second sample ($n_2 = 381$) was used to confirm the structural validity of environmental and persistence scales through confirmatory factor analyses and to compare this new structure to Kember et al. (1994)' subscales. While the latter resulted in an insufficient model fit, the new environmental and persistence scales yielded a very good model fit with strong goodness-of-fit indices and statistics. These results confirmed the structural validity of the new scales, which can trustfully be used in further empirical studies related to online student persistence. The new scales can also be used by practitioners to detect at-risk students early in a semester, allowing to offer them specific individual support to foster student persistence in online courses.

Keywords

Higher education; online courses; student persistence; environmental factors; scale development; factor analysis.

1. Introduction

The number of online courses is rising in higher education (Johnson, 2019; Seaman et al., 2018). For example, in Canada, 76% of institutions were offering such courses in 2019. The proportion went up to 92% of institutions with enrollments above 7,500 and 93% of universities (Johnson, 2019). Online courses registrations grew by 10% between 2016-17 to 2017-18 and were expected to rise further in the next years (Johnson, 2019).

The popularity of online courses notably results from the increasing diversity of student population. Along with typical distance, adult students who cannot access on-campus courses because of personal or professional constraints, online courses now also include lifelong learners or on-campus students registering in some online courses for advancing their academic background while benefitting from an increased flexibility compared to face-to-face courses (Lee, 2017). Indeed, flexibility in terms of time, place or even study pace is the main advantage of online courses, which allows students to balance their academic, personal and professional lives (Blackmon & Major, 2012). Furthermore, with the current pandemic COVID-19 forcing students to stay at home and instructors to move their courses online, one can expect an increased focus on online learning in the future years (Contact North, 2020).

Despite the growing popularity of online courses, student persistence in these courses is still perceived as a major challenge (Hobson & Puruhito, 2018; Johnson, 2019; Li & Wong, 2019; Yang et al., 2017). According to Croxton (2014), online student persistence range from the lowest 25% to as high as 90%. In Open Universities, a recent report of the Commonwealth revealed that the average ratio of students exiting with a qualification over enrollments was only about 15%, suggesting a very low persistence rate of students in online courses (Commonwealth of Learning, 2017). Student persistence in online courses is also known as a complex phenomenon that can be affected by multiple factors (Choi & Park, 2018; Yang et al., 2017). Based on literature reviews, several authors presented and classified such factors influencing online student persistence, e.g., student characteristics and skills, institutional variables such as course design or support, as well as environmental barriers or facilitators from work, family or friends (Hart, 2012; Lee & Choi, 2011; Muljana & Luo, 2019). In the current situation where lots of students have to turn to online learning due to the COVID-19 pandemic, environmental factors may play an important role in student persistence. For instance, Fetzner (2013) found that environmental barriers were in the top three of twenty-two reasons for students' withdrawal or failure in online courses, accounting for 47.6% of reported reasons (n=438). Students' feelings of isolation and lacking support from work, family or friends or experiencing difficulties related to personal or professional constraints may have a large impact on student persistence in online courses. Therefore, such influences should be properly measured in order to conceive and implement countering strategies.

Student persistence in online courses has been the focus of numerous studies in literature for more than twenty years. However, Lee and Choi (2011) indicated that the generalizability of findings was often limited by small sample sizes and single online course or program. Choi and Park (2018) also argued that student persistence in online courses needs to be studied empirically and at large scale to identify its significant influential factors and the exact relationships between these. Nevertheless, the empirical study of factors influencing student persistence in online courses needs operationalizable indicators and specific scales. Especially, few empirical publications investigated environmental factors facilitating or hindering online student persistence (Lee & Choi, 2011; Li & Wong, 2019). Only Kember (1995) proposed detailed scales, labelled social integration and external attribution, with items referring to environmental factors that may influence persistence in online courses, particularly for adult and lifelong learner students. However, the results relying on this scale published so far (Kember, Lai, Murphy, Siaw, & Yuen, 1992, 1994; Kember, 1995; Woodley, de Lange, & Tanewski, 2001) did not provide reliable subscales of items, though they still serve as an interesting starting point. Inspired from Kember (1995)'s social integration and external attribution scales and corresponding items, this study aims at presenting reliable and valid scales for studying environmental facilitators or barriers related to student persistence in online courses.

2. Conceptual background and literature review

2.1 Online student persistence frameworks

Several frameworks have been proposed in the literature as attempts to explain and conceptualize student persistence in online courses (e.g., Kember, 1995; Park & Choi, 2009; Rovai, 2003). Most of these were inspired by the Student Integration Model (Tinto, 1975), which is one of the most popular frameworks to explain dropout or persistence. In Tinto's framework, students' individual characteristics and background determine both their goal and individual commitments when entering an academic system, next influenced by their academic and social integration that subsequently lead to their decision to drop out or persist in higher education. However, this framework was developed for on-campus and traditional students, assuming extensive student-student and student-faculty interactions as part of their academic and social integration.

Kember (1989,1995) adapted Tinto's framework to adults studying at a distance, by enlarging social integration to the influence of family, work or even friends onto persistence, arguing that these may have a greater importance than student-student or student-faculty interactions. He also incorporated an external attribution factor consisting of negative events or constraints hindering studies. In the Distance Education Student Progress Model (Kember, 1995), social integration leads to academic integration in contrast with external attribution leading to academic incompatibility. Given academic integration or incompatibility, students analyze the costs and benefits to persist or drop out in online courses and make their decision accordingly. The model also includes a recycling loop accounting for the diverse life changes of adult students, who can later decide to reenter online courses.

Rovai (2003)'s Composite Persistence Model distinguished relevant factors prior to admission (i.e., students' characteristics and skills) from internal factors after admission consisting of diverse components such as Tinto's academic and social integration of students, their goal and individual commitments, but also students' needs and study habits and the pedagogy (teaching and learning styles). Factors prior to admission as well as external factors after admission (such as finances, work and family responsibilities, outside encouragements and events) influence internal factors after admission, which subsequently lead to the students' decision to persist in online courses. Park (2007) revisited Rovai (2003)'s model by moving external factors between *prior to* and *during* online courses, accounting for the possibility that students may drop out a course due to preexisting external events or constraints. She also introduced a bidirectional link between external and internal factors that interact with each other (Park & Choi, 2009). Furthermore, the internal factors were grouped into social integration, academic integration, technological issues and lack of motivation. During an online course, both external and internal factors influence the decision of a student to persist or drop out.

Apart from these conceptual frameworks, several authors sought to list and classify the factors influencing student persistence in online courses based on literature reviews. These reviews are presented in the next section.

2.2 Literature review about factors influencing online student persistence

Lee and Choi (2011) reviewed the literature on persistence and dropout in online courses from 1999 to 2009 in order to identify influential factors and strategies to address these. Having examined 35 publications, they classified 69 influential factors into three categories: students, course/program and environmental. Student factors included academic background, relevant experiences and skills as well as psychological attributes. Course/Program factors referred to course design, institutional support and interactions. Finally, environmental factors concerned students' work commitments and supportive environment, which included life or work changes, events or particular circumstances. The review study also presented a summary of strategies to address influential factors of persistence or dropout. These were "(a) understanding each student's challenges and potential, (b) providing quality course activities and well-structured supports, and (c) handling environmental issues and emotional challenges" (p. 593). The authors also indicated that while student factors accounted for 55% of the number of influential factors in the selected studies, the course/program as well as environmental factors only accounted for 20% and 25%, respectively. They invited to pursue further research in these directions, arguing that the students' behaviors (i.e., decisions to persist or drop out) are influenced by the context (course and/or program) and their environment (outside the academic institution). In contrast, they indicated not to have included students' demographic characteristics such as age or gender in the dropout factors, because findings were inconclusive in that regard.

Hart (2012) conducted a similar literature review about influential factors to persistence or dropout in online courses and selected 20 publications after 1999. She identified 10 facilitators of persistence, e.g., students' factors such as social connectedness or presence, GPA, goal commitment, course/program factors such as quality of interactions and feedback, satisfaction and relevance, as well as a support factor from family, friends, colleagues or even other students and faculty through an online learning community. She also presented 8 barriers to persistence, e.g., students' factors such as basic computer skills or lack of computer accessibility, course/program factors such as difficulty in accessing resources or poor communication, and non-academic issues such as work or family responsibilities, changes and events, illness or financial difficulties. Specifically, the author indicated that non-academic issues "can be mitigated by the presence of strong support and social connections within the course" (p. 38).

Lee and Choy (2011) and Hart (2012) also indicated a lack of consistency in addressing persistence or dropout in online courses. Some authors defined persistence in terms of course completion indicated by students' final grades (e.g., Liu et al., 2009), others defined dropout as withdrawing from a course "while acquiring financial penalties" (Levy, 2007, p. 188). Oher authors considered that persistent students are those who enroll to courses for consecutive semesters (e.g., Pierrakeas, Xenos, Panagiotakopoulos et Vergidis, 2004). Lee and Choy (2011) suggested that future studies should provide a clear and consistent definition of persistence or dropout in online courses.

Very recently, Muljana and Luo (2019) conducted a literature review on persistence or dropout factors in online courses as well as recommended strategies. They selected 40 publications from 2010 to 2018 by focusing on influential factors related to (a) the academic institution, (b) the instructor, course or faculty and (c) the student. At the institutional level, the influential factors were institutional support and curriculum or program level of difficulty. At the instructor level, the influential factors concerned "facilitation of student engagement and promotion of a sense of belonging" (p. 28), facilitation of learning and course design. At the student level, the influential factors referred to individual skills, demographic characteristics and other personal influences corresponding to Lee and Choy (2011)' environmental factors or Hart (2012)'s non-academic issues. For instance, Muljana and Luo (2019) mentioned family support, work and family responsibilities, financial issues or illness. The authors also provided several recommended strategies to enhance students' persistence in online courses. These concerned early interventions targeting students, continuous support of students, professional development and assistance for faculty in online courses, student-instructor interactions, course design and delivery as well as synergy among stakeholders for enhancing online courses or support to online students.

Laurie et al. (2020), as for them, conducted a systematic literature review to identify influential factors of persistence in higher (online) education and effective strategies to address this issue. They selected 10 and 16 publications for influential factors and strategies, respectively. However, note that their study was not restricted to online courses. In addition to 'non-modifiable' demographic and individual characteristics of students, they classified the 'modifiable' influential factors of persistence into (a) dispositional cognitive (e.g., learning strategies) and non-cognitive (e.g., self-efficacy), (b) situational factors (employment and supportive network) and (c) institutional factors (faculty-student interaction). The situational factors here correspond to Lee and Choy (2011)' environmental factors, although the authors did not discuss these in detail. Several strategies were also presented to address the student persistence issue like coaching and remedial teaching, peer mentoring, motivational contact, academic dismissal policies and interventions on instruction, with only the third and last one being proposed in online contexts.

Among the numerous factors influencing student persistence or dropout in online courses that were classified in the previous literature reviews (see Table 1), this study targets environmental factors from Lee and Choy (2011), elsewhere labelled non-academic issues (Hart, 2012), other personal influences (Muljana & Luo, 2019) or situational factors (Laurie et al., 2020), that particularly concerns adult or lifelong learner students. Empirical studies targeting such factors are presented in the next section, as well as the goal of this study.

Table 1. Summary of influential factors to student persistence in online courses

Students' factors	• Academic background, relevant experiences and skills, psychological attributes (Lee & Choi, 2011) • Facilitators (social connectedness or presence, GPA, goal commitment) and barriers (basic computer skills or lack of computer accessibility) (Hart, 2012) • Individual skills, demographic characteristics (Muljana & Luo, 2019) • Dispositional cognitive (learning strategies) and non-cognitive (self-efficacy) factors (Laurie et al., 2020)

Course/program/ institutional factors	• Course design, institutional support and interactions (Lee & Choi, 2011) • Facilitators (quality of interactions, feedback, satisfaction, relevance) and barriers (difficulty in accessing resources, poor communication) (Hart, 2012) • Facilitation of learning and student engagement, course design; Institutional support, curriculum or program level of difficulty (Muljana & Luo, 2019) • Faculty-student interaction (Laurie et al., 2020)
Environmental factors	• Students' work commitments, supportive environment, life or work changes, events or particular circumstances (Lee & Choi, 2011) • Facilitators (support from family, friends, colleagues or even an online learning community) and barriers (work or family responsibilities, changes and events, illness or financial difficulties) (Hart, 2012) • Personal influences such as family support, work and family responsibilities, financial issues or illness (Muljana & Luo, 2019) • Employment and supportive network (Laurie et al., 2020)

2.3 Empirical studies about environmental factors influencing online student persistence and research goal

Classified as a specific category of influence, environmental factors have not received significant attention in empirical studies so far (Lee & Choi, 2011; Li & Wong, 2019). Including family, work and friends support, events or life changes such as illness or an increase of workload, such factors can however affect student persistence in online courses (Aragon & Johnson, 2008; Choi & Park, 2018; Holder, 2007; Ivankova & Stick, 2006; Park & Choi, 2009; Sorensen & Donovan, 2017). For instance, Choi and Park (2018) tested a path-analysis model on a large administrative dataset of 2129 students that were admitted to an online university of South Korea in 2013 and 2014, among which 45.3% (964) had dropped out at the time of the study. First, they indicated that 42.4% (409) of dropout students had taken a leave of absence (granted by the university for students encountering personal, family or work issues) for at least a semester, compared to only 9.3% (108) of persistent students. The number of semesters where students had taken a leave of absence, labelled 'physical constraints' in the study, resulted in significant negative correlations

($p<0.0001$) with a persistence/dropout variable, but also with other variables including satisfaction, interaction with course content and GPA. All paths linking physical constraints and other variables were also significant and negative, showing that students experiencing personal, family or work issues were more at risk to drop out. While Choi and Park (2018)' recent publication provided strong arguments to include environmental factors in future studies about student persistence in online courses, their results were limited by the way they operationalized physical constraints of students, i.e., the number of semesters where students had taken a leave of absence from the university. To obtain more detailed and precise results about environmental factors influencing student persistence or dropout in online courses, specific scales need to be developed and tested.

Environmental factors were often operationalized through a small number of items, going from a single ("I became too busy with work and/or family", Sorensen & Donovan, 2017, p. 212) to eight items (Ivankova & Stick, 2006). The items were also usually shown little attention. For instance, Ivankova and Stick (2006) only mentioned that these related to family or significant others and employment but they did not present any item example. Furthermore, the reliability and validity of scales relating to environment factors were given little importance. For instance, Ivankova and Stick (2006) reported Cronbach's α of 0.58 for family or significant others and 0.53 for employment items without any further discussion. Holder (2007) disclosed 3 items for emotional support and 4 items for fiscal support (two of them being more like a cost/benefit analysis of persisting in education) with Cronbach's α of 0.43 and 0.59, respectively. Selecting only 4 items among the ones presented by Holder (2007) to evaluate student support from work and family, Lee, Choi and Kim (2013) obtained a Cronbach's α of 0.72. Finally, Park an Choi (2009) used 6 items for work and family support for which they obtained Cronbach's α of 0.83 and 0.78, respectively. Although these were not presented in full, the authors provided examples of items for both categories.

However, going back in the literature about persistence or dropout in online courses leads to Kember's Distance Education Student Progress Model, designed for distance adult students, in which environmental factors were operationalized through 25 items of social integration and external attribution in the Distance Education Student Progress Inventory (DESP) (Kember et al., 1994; Kember, 1995). More specifically, the social integration scale consisted of enrollment encouragement, study encouragement and family support (11 items in total). The external attribution scale encompassed insufficient time, events hinder study, distractions (14 items) as well as 3 items that were related to potential dropout of students. Although the DESP also included 3 items related to the costs and benefits to persist or drop out in online courses, no empirical results were presented for this subscale. The reliability and validity of the social integration and external attribution scales and subscales were tested on students (n = 555) from online courses in three Hong Kong institutions (Kember et al., 1994; Kember, 1995). Cronbach's α of 0.67 and 0.68 were reported for the social integration and external attribution scales, respectively (replication study, see Kember, 1995). They were respectively of 0.46, 0.49 and 0.48 for enrollment encouragement, study encouragement and family support. For the external attribution subscales, they were respectively of 0.77, 0.55 and 0.56 for insufficient time, events hinder study and distractions. Using principal components analyses, the authors also presented a second-factor model that included both social integration (renamed 'emotional support') and external attribution scales, in addition to other academic accommodation and incompatibility scales that were more specific to students' academic integration. The social integration/emotional support scale accounted for 13.20% of data variability, while the external attribution scale represented 20.80% of data variability.

More recently, Woodley et al. (2001) replicated Kember and colleagues' studies by testing it in four courses at the Open University of the United Kingdom (n = 427). Using a slightly modified version of the DESP, they obtained Cronbach's α of 0.72 for social integration and 0.75 for external attribution. However, Cronbach's α were predominantly below the acceptance level of 0.70 for the corresponding subscales, with only insufficient time (0.70) and distraction (0.72) demonstrating an acceptable internal consistency. Using principal components and confirmatory analysis, they also demonstrated the lack of validity of Kember and colleagues' scales and subscales, notably exhibiting crossloadings between items and poor model fit for both social integration and external attribution.

Even though Kember and colleagues' (1994, 1995) DESP scales and subscales showed poor reliability results, they provided a large set of operationalizable indicators to study environmental factors influencing persistence in online courses, which are particularly suitable for adult or lifelong learner students. This study starts from these indicators to build reliable and valid scales of environmental and persistence factors in online courses.

3. Method

3.1 Measure

Kember and colleagues (1994, 1995)' social integration and external attribution items were used in this study. Social integration included 4 items for enrollment encouragement (EnrollEnc1 to EnrollEnc4), 4 items for study encouragement (StudyEnc1 to StudyEnc4) and 3 items for family support (FamSup1 to FamSup3). External attribution was composed of 4 items related to insufficient time (InsuffTime1 to InsuffTime4), 3 items for events hindering study (Events1 to Events3), 7 items for distractions (Distractions1 to Distractions7). For the sake of clarity, the previous 25 items are referred as the *environmental items* in the remainder of this study. The 3 items for potential dropouts (PotDrop1 to PotDrop3) as well as 3 cost-benefit items (CostBenef1 to CostBenef3) presented by Kember and colleagues (1994, 1995) were also used in this study. All items were translated in French by independent professional translators. Furthermore, 3 additional items related to student persistence in online courses were added by the principal researcher of this study (PotDrop4 to PotDrop6). These items were borrowed from previous studies (Lakhal, 2019). In what follows, the 9 potential dropout and cost-benefit items are referred as the *persistence items*. All environmental and persistence items used in this study are detailed in the Appendix. Finally, a 7-point Likert scale was used to allow a large variability in student answers, coded from 1 = "strongly disagree" to 7 = "strongly agree".

3.2 Sample and procedure

During Winter 2016, all students enrolled in online courses at two French-speaking universities in eastern Canada were invited to fill an online research survey on a purposeful basis. A total of 835 students participated to the research survey, the data of which were randomly split into two samples of size $n_1 = 417$ (S1) and $n_2 = 418$ (S2). After elimination of participants with missing data and potential outliers, the final samples included 385 (S1) and 381 (S2) participants, respectively. Although no a priori criterion was used, the sample sizes followed the recommended levels of at least 300 participants and 10 participants per survey item for scale development in social sciences (Boateng et al., 2018; DeVellis, 2016). Individual characteristics of participants in these samples are presented in Table 2.

Table 2. Individual characteristics of participants

	Sample	Relative frequencies
Gender	S1	72.2% F; 27.8% M
	S2	74.3% F; 25.7% M
Age (years)	S1	43.3% ≤25; 27.3%]25-35]; 18.5%]35,45]; 10.9% >45
	S2	38.1% ≤25; 31.2%]25-35]; 19.7%]35,45]; 11% >45
Family responsibilities	S1	18.4% low; 33.5% medium; 48.1% high
	S2	17.6% low; 31.5% medium; 50.9% high
Work (hours/week)	S1	20.3% none; 10% [1-10]; 19.4% [11-20]; 10.3% [21-30]; 30.6% [30-40]; 6.4% >45
	S2	16.3% none; 3.9% [1-10]; 16.8% [11-20]; 12.1% [21-30]; 37.8% [30-40]; 13.1% >45

3.3 Data analysis

The first sample S1 was used to explore the data set and to uncover valid and reliable environmental and persistence scales. Then the second sample S2 was used to confirm the construct validity of environmental and persistence scales.

Principal component analyses (PCA) and reliability analyses were first performed on the first sample S1 using SPSS 25. The PCA aimed to uncover the environmental and persistence factors underlying the data in a context where the relationships were unknown (Byrne, 2006; Yong & Pearce, 2013). Following the literature recommendations, items showing low communalities (<0.32) or cross-loadings on several factors (≥0.32) were eliminated (Tabachnick & Fidell, 2007). New PCA were carried out until the obtention of a simple structure that was also conceptually grounded (Pituch et Stevens, 2016; Tabachnick et Fidell, 2007; Worthington et Whittaker, 2006). Next, reliability analyses were used to improve and later confirm the internal consistency of each resulting factor. Item-item and item-scale correlations were first examined. Items showing low correlations (<0.32) or low item-scale correlations (<0.40) were removed since these demonstrated a poor internal consistency with other items (Tabachnick & Fidell, 2007). Cronbach's α and item-scale correlations then confirmed the internal consistency of each factor (Tabachnick & Fidell, 2007).

Next, confirmatory factor analyses (CFA) were performed on the second sample S2 using EQS 6.2 (Bentler, 2006). The CFA aimed to confirm the environmental and persistence factors obtained through PCA, as well as to compare the obtained results to those of CFA for Kember and colleagues' (1994) DESP subscales. The default maximum likelihood method was invoked with a robust option in EQS, allowing to treat categorical and possibly non-normal data as continuous (Bentler & Chou, 1987). With the robust option, EQS computes a Satorra and Bentler (1988) chi-square statistic and robust versions of fit and misfit indexes. The literature then suggests relying on various indices and statistics to evaluate a model fit to the data (Byrne, 2006; Jackson et al., 2009; Schreiber et al., 2006). In addition to report the chi-square statistics and degrees of freedom for which a ratio χ^2/df below 3 is recommended for model acceptance (Jöreskog, 1993; Schreiber et al., 2006), we reported the non-normed fit index (NNFI), the comparative fit index (CFI), the standard root mean square residual (SRMR) and the root-mean-square error of approximation (RMSEA) and corresponding 90% confidence interval. The goodness-of fit indices NNFI and CFI are considered as acceptable if as high as 0.90 (P. M. Bentler & Bonett, 1980; McDonald & Ho, 2002) and a good fit at 0.95 (Hu & Bentler, 1999; Schreiber et al., 2006). The residual based fit indices SRMR and RMSEA are acceptable below 0.08 (McDonald & Ho, 2002) and a good fit below 0.06 (Schreiber et al., 2006).

4. Results

4.1 Preliminary analyses

As a first preliminary test, the internal consistency of Kember and colleagues' (1994) DESP subscales was tested on the sample S1 by computing the corresponding Cronbach's α. These are presented in Table 3 in comparison to the ones obtained in Kember et al. (1994) replication study and Woodley et al. (2001) study.

Table 3. Cronbach's α for DESP subscales, on the sample S1 and compared to previous results from the literature

	Kember et al. (1994)	Woodley et al. (2001)	This study (sample S1)
Enrollment encouragement	0.46	0.58	0.90
Study encouragement	0.49	0.61	0.66
Family support	0.48	0.62	0.51
Insufficient time	0.77	0.70	0.83
Events hinder study	0.55	0.66	0.74
Distractions	0.56	0.72	0.55
Potential dropout	0.66	0.59	0.57

Although the Cronbach's α obtained with S1 were higher than those reported previously in the literature for several DESP subscales, four subscales were still under the usual acceptance level of 0.70, thus demonstrating poor internal consistencies among items (Tabachnick & Fidell, 2007). These results confirmed the need to explore all environmental items as a whole to uncover the underlying patterns in the data.

Next, correlations were computed between all items. Since two items (InsuffTime1 and InsuffTime2) showed a correlation of 0.90, one of them (InsuffTime1) was eliminated to avoid risk of multicollinearity. Seven items (FamSup1, FamSup2, Distractions2, Distractions4, Distractions6, Distractions7 and CostBen3) were also removed because they showed only one or none correlation above 0.30 with other items (Pituch & Stevens, 2016; Yong & Pearce, 2013). For the remaining environmental items, significant correlations ($\geq$ 0.30) ranged from 0.31 to 0.83 with a low average item-item correlation of 0.21. For persistence items, significant correlations ranged from 0.33 to 0.82 with a medium average item-item correlation of 0.46. No sign of multicollinearity was detected as all correlations were <0.90 and variance inflation factors <10 (Alin, 2010; Tabachnick & Fidell, 2007).

4.2 Building a valid and reliable scale of environmental and persistence factors

4.2.1 Environmental factors

For the remaining environmental items, the Kaiser-Meyer-Olkin (KMO) index was 0.77, with a significant Bartlett test (p=0.000) and a correlation matrix determinant of 0.0003 above the minimum level 0.00001 (Tabachnick & Fidell, 2007; Yong & Pearce, 2013). These confirmed the factorability of the correlation matrix and the sample adequacy for factor analyses.

Principal components analysis (PCA) was performed with varimax rotation since most correlations between items of different DESP subscales were below 0.30 (also confirmed by a preliminary oblique rotation resulting in low correlations between factors). It resulted in five factors with eigen values 4.25, 3.42, 1.74, 1.30 and 1.04, the last two eigen values being very close to the minimum acceptance level of 1. To avoid overestimating the number of extracted factors, the scree plot was also inspected as recommended in the literature (Costello & Osborne, 2005; Yong & Pearce, 2013), which suggested a three factor solution.

A PCA was then carried out by imposing the number of factors to three. These accounted for 23.59, 19.00 and 9.68% of the data variability, for a total of 52.27%. One item (FamSup3) was then removed because it showed a low communality of 0.20<0.32 with all other items, as well as three items (StudyEnc1, StudyEnc4 and InsuffTime3) with loadings above 0.32 on several factors (Pituch & Stevens, 2016; Tabachnick & Fidell, 2007).

The next PCA resulted in a simple structure with three factors that were also conceptually grounded (Pituch & Stevens, 2016; Tabachnick & Fidell, 2007; Worthington & Whittaker, 2006). The first factor (F1) labelled 'encouragements' (28.33% of data variability) was composed of all remaining enrollment and study encouragement items. The second factor (F2) labelled 'time-events barriers' (21.44% of data variability) included the remaining insufficient time and events items, as well as an item referring to children interfering with studies (Distractions5). The third and last factor (F3) labelled 'external interests' (10.16% of data variability) was composed of only two items (Distractions1, Distractions3) expressing student preference and choice to do other things than studying. The three factors explained a total of 59.92% of data variability.

Next, a reliability analysis was performed on each of the three resulting factors. For F1, one item (StudyEnc3) was eliminated because it presented low correlations with several other items and a corrected item-scale correlation of 0.45 close to acceptance level of 0.40. A new reliability analysis on F1 yielded satisfactory results, with Cronbach α of 0.89 and corrected item-scale correlations between 0.51 and 0.85 demonstrating a good internal consistency between items. Only one item (StudyEnc2) showed a low squared multiple correlation (R^2) of 0.35, which is the proportion of item variance accounted for by the factor (Worthington & Whittaker, 2006). However, it was preserved to avoid overfitting the model. All other R^2 ranged from 0.62 to 0.76. For F2, two items (InsuffTime2 and Distractions5) presented low correlations with several other items and corrected item-scale correlations (0.43, 0.46) close to the acceptance level of 0.40. Removing these items yielded satisfactory results with Cronbach α of 0.81, corrected item-scale correlations between 0.59 and 0.70, and R^2 between 0.45 and 0.70. For F3, it resulted in a poor Cronbach α of 0.62 and a R^2 of 0.20. Furthermore, the item-item correlation was 0.45 below the recommended correlation level of 0.70 for two-item factors, and it was removed accordingly (Yong & Pearce, 2013). A final PCA resulted in an environmental scale with two factors accounting for a total of 67.15% of data variability, presented in Table 4 (see detailed items in the Appendix).

Table 4. Saturations and communalities (h^2) for the final environmental scale

	Encouragements	Time-Events	h^2
EnrollEnc1	0.91		0.83
EnrollEnc2	0.91		0.83
EnrollEnc3	0.82		0.69
EnrollEnc4	0.85		0.72
StudyEnc2	0.64		0.41
InsuffTime4		0.82	0.68
Events1		0.86	0.74
Events2		0.75	0.56
Events3		0.76	0.58
Explained variability (%)	*39.35*	*27.80*	
Cronbach α	*0.89*	*0.81*	

4.2.2 Persistence factors

For the persistence items, the KMO index was 0.79 (Bartlett test p=0.000) and a correlation matrix determinant of 0.02 above 0.00001, which confirmed the factorability of the correlation matrix (Tabachnick & Fidell, 2007; Yong & Pearce, 2013). A PCA with oblimin rotation was performed since persistence items demonstrated an average medium correlation (0.46, see preliminary results). It resulted in two factors with eigen values of 3.84 and 1.29 that accounted for 48.01% and 16.08% of data variability, for a total of 64.10%. However, one item (PotDropout3) showed a low communality of 0.23 and it was eliminated. A new PCA resulted in a simple structure that was also conceptually grounded, with the first factor related to potential dropout items and the second factor to cost-benefit items. A reliability analysis was conducted for each factor and it demonstrated satisfactory results. For the potential dropout items, Cronbach α was 0.86, item-scale correlations ranged from 0.49 to 0.83 and R^2 from 0.36 to 0.77. For the cost-benefit items, Cronbach α

was 0.79 with a correlation of 0.67 between the two items ($R^2 = 0.43$). Although that the correlation was a little below the recommended level of 0.70 for factors with only two items (Worthington & Whittaker, 2006), alternative tests grouping potential dropout and cost-benefit items showed that the two factor solution was best. The correlation between both potential dropout and cost-benefit factors was 0.35. The results of a final PCA for the persistence scale are presented in Table 5 and accounted for a total of 70.80% of data variability (see detailed items in the Appendix).

Table 5. Saturations and communalities (h^2) for the final persistence scale

	Potential dropout	Cost-benefit	h^2
PotDrop1	0.75		0.56
PotDrop2	0.75		0.67
PotDrop4	0.87		0.82
PotDrop5	0.92		0.82
PotDrop6	0.70		0.45
CostBen1		0.90	0.83
CostBen2		0.91	0.81
Explained variability (%)	*52.49*	*18.30*	
Cronbach α	*0.86*	*0.79*	

4.3 Confirming the structure validity of environmental and persistence scales

The new environmental and persistence scales were next tested using CFA on the second sample S2, as well as compared to similar tests for Kember and colleagues' (1994) DESP subscales. Since Mardia's normalized estimate (137 > 5.00) indicated non-normally distributed data for the sample S2, the robust option was invoked for all following tests in EQS to obtain corrected standard errors, fit indices and statistics.

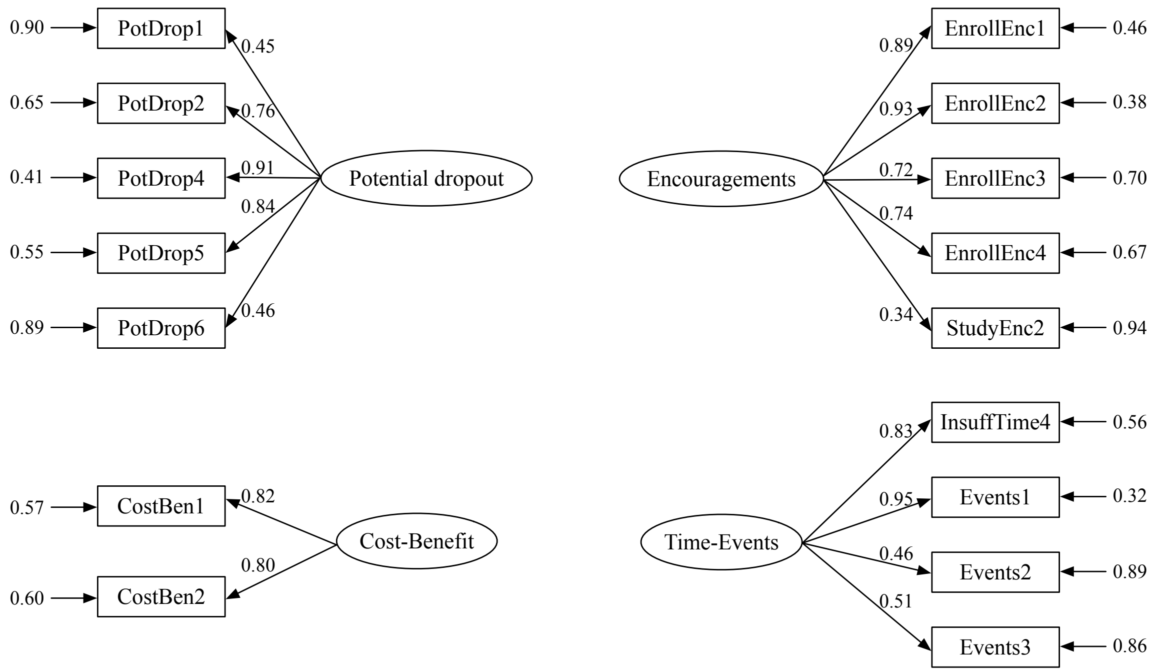
Several models were tested, beginning with the seven DESP subscales (Enrolment encouragement to potential dropout, see Appendix). An improved version of the DESP was also tested replacing the potential dropout subscale by the new persistence scale (as described in Table 4), labelled DESP_I in the following results. Next, the new environmental and persistence scales were simultaneously tested, labelled New_Env_Pers in the following results. Following a Lagrange Multiplier test (Byrne, 2006), three error covariance parameters were also included in the models. These all sounded theoretically grounded (Byrne, 2006; Schreiber et al., 2006) and were between EnrollEnc1 and StudyEnc2 (partner encouragements), Events2 and Events3 (unexpected circumstances), as well as PotDrop5 and PotDrop6 (imminent dropout of online course).

The values of chi-square statistics, fit and misfit indices of the tested models are described in Table 6. The DESP subscales resulted in a poor χ^2/df ratio of 3.35 > 3.00 as well as fit indices (0.76, 0.78) below the minimal acceptance level of 0.90. Misfit indices are around the acceptance level of 0.080. The improved DESP_I including the new persistence scale yielded somewhat better results, with an χ^2/df ratio of 2.95 < 3.00 around the acceptance level and acceptable misfit indices (0.077 and 0.072 < 0.080). However, the fit indices (0.78, 0.80) are still far below the minimal acceptance level. Finally, the new environmental and persistence scales showed a very good model fit to the data, with an excellent χ^2/df ratio of 1.64 < 3.00, as well as very good fit indices (0.96, 0.97 > 0.95) and misfit indices (0.053, 0.041 < 0.060). The final standardized solution is presented in Figure 1.

Table 6. Statistics, fit and misfit indices obtained through CFA

	Satorra-Bentler	NNFI	CFI	SRMR	RMSEA
DESP	$\chi^2(337) = 1129$	0.76	0.78	0.080	0.079 [0.073; 0.084]
DESP_I	$\chi^2(447) = 1320$	0.78	0.80	0.077	0.072 [0.067; 0.076]
New_Env_Pers	$\chi^2(98) = 161$	0.96	0.97	0.053	0.041 [0.029; 0.052]

Figure 1. Standardized solution of CFA for environmental and persistence scales



5. Discussion and conclusions

This study aimed at building a reliable and valid scale to study environmental facilitators or barriers related to student persistence in online courses, that are particularly suitable for adult or lifelong learner students. Drawing on Kember and colleagues (1994)' social integration and external attribution scales and subscales as a starting point, data collected in two French-speaking eastern Canadian universities during Winter 2016 were randomly split into two samples. The first sample ($n_1 = 385$) was used to explore the data set through principal component and reliability analyses. These confirmed a two-factor environmental scale composed of five encouragements items (factor 1) and four time-events items (factor 2), as well as a two-factor persistence scale that included five potential dropout items (factor 3) and two cost-benefit items (factor 4). All factors also showed a very good internal consistency with Cronbach α between 0.79 and 0.89 and high communalities, thus demonstrating a high proportion of common variance between items of each factor. Next, the second sample ($n_2 = 381$) was used to confirm the structural validity of both environmental and persistence scales through confirmatory factor analyses, as well as to compare this new structure to Kember and colleagues (1994)' subscales. The latter resulted in an insufficient model fit to the data as expected, since Kember et al. (1994)' subscales have never proved to be reliable or valid as such in the previous literature. Nevertheless, the new environmental and persistence scales yielded a very good model fit to the data. Strong goodness-of-fit and residual-based fit indices and statistics confirmed the structural validity of the new scales.

The environmental scale resulted in facilitators (encouragements) and barriers (time-events) of student persistence in online courses, echoing a simple classification as proposed by Hart (2012). It allowed to detail the external factors from Rovai (2003) or Park and Choi (2009) into encouragements and time-events facilitating or hindering online student persistence. Such factors can appear prior (e.g., encouragements to enroll) or during (e.g., personal or work circumstances) an online course, in line with Park and Choi (2009)' framework. These factors were validated through two large samples collected in various online courses, as recommended by Lee and Choi (2011) or Choi and Park (2018). The shortness of the new scale is also beneficial. Indeed, it means that it can easily be tested along with other scales related to individual characteristics, institution variables or course design and support in future research. Furthermore, a persistence scale was also proposed in this study, allowing to precisely test for online student persistence. It provides researchers a clear scale to test student intention to persist or drop out from an online course. If conducted quite early in a semester, such scales can bring numerous information on factors influencing student persistence in online courses, which will be the focus of a next research. In particular, future studies could measure the effects of encouragements and time-events factors on the students' cost-benefit and potential dropout analysis, and finally on their persistence or dropout decision. To our knowledge, they are the first environmental and persistence scales for online student persistence of which the reliability and validity was investigated in detail. This is also the first time that such scales are available for French-speaking researchers.

The study however has some limitations. First, the standardized solution showed some high measurement error values. However, strong saturations were obtained for both samples.

Although further item eliminations could eventually prevent this, it could also weaken the obtained scales by narrowing them too much. The robustness of the new scales will be assessed in future studies, in conjunction with other influential factors of student persistence, e.g., individual characteristics. Furthermore, it could be argued that it is presented at a conceptual level only. Yet, the statistical investigation of reliability and validity of scales requires precise and detailed analyses, therefore the focus of this study to better inform future empirical studies about online student persistence.

Although presented from a conceptual and statistical standpoint, this study also has important and actionable impacts for practitioners and administrators. Indeed, it provides a reliable and valid scale to measure environmental facilitators and barriers to student persistence in online courses, as well as a scale to measure potential dropout and cost-benefit analysis yielding to student persistence or dropout decisions. By using such a scale early in a semester, instructors and/or administrators could obtain sensitive information about their students and act on it. For instance, instructors could better support students lacking external encouragements or facing personal/work difficulties. Programs or institutions could make use of early detection of at-risk student populations to conceive and implement specific support, helping to increase student persistence in online courses. In light of the current pandemic and its contingency to last for years while transforming the higher education towards blended and online learning, early detection of environmental factors and potential dropout decisions are crucial to foster student persistence.

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7. Appendix

7.1 Environmental and persistence items

Initial items adapted from Kember (1995):

EnrolEnc1. My partner encouraged me to enroll in this online course.

EnrolEnc2. My family encouraged me to enroll in this online course.

EnrolEnc3. My employer encouraged me to enroll in this online course.

EnrolEnc4. My friends encouraged me to enroll in this online course.

StudyEnc1. My employer was supportive while I was studying.

StudyEnc2. My partner offered support while I was studying.

StudyEnc3. My workmates encouraged me to study.

StudyEnc4. My family encourages me to study because they think the qualification is important.

FamSup1. I usually spend a lot of time with my family.

FamSup2. *I do not need the support of my family to succeed in this online course.

FamSup3. The support of my family means a lot to me.

InsuffTime1. As I work long hours it is difficult to find time to study.

InsuffTime2. Long hours at work leave me little time for study.

InsuffTime3. I seem to have so many other things to do there is never enough time for study.

InsuffTime4. A change in my work left me without enough time to study.
Events1. A change in my work situation made it difficult to complete this online course.
Events2. I got sick during this online course, so found it difficult to keep up.
Events3. Personal/family circumstances, unseen at the time of enrollment, have hindered my studies.
Distractions1. I prefer to spend time doing things other than studying.
Distractions2. I have a busy social life.
Distractions3. I go out a lot, rather than studying.
Distractions4. My partner is annoyed that I spend so much time studying.
Distractions5. My children interfered with my studies.
Distractions6. *I do not let anything interfere with my studies.
Distractions7. My friends wanted me to go out rather than study.
PotDrop1. *I am very determined to finish this online course.
PotDrop2. I often consider dropping out from this online course.
PotDrop3. I often wonder whether all the study is worth the effort.
CostBen1. As I continue with my online course work, I continually weigh the pros and cons of the costs of staying in the online program.
CostBen2. As I continue taking online courses, I continually ask myself if the financial cost is 'worth it' to continue.
CostBen3. The benefits of continuing with my online education outweigh the financial sacrifices made.

Additional persistence items ([Authors], 2019):
PotDrop4. I am undecided as to whether to finish this online course.
PotDrop5. I am about to drop out of this online course.
PotDrop6. I have already dropped out of this online course.

(* those items have to be reverse coded before analysis)

7.2 Final environmental and persistence scales as translated in French

Encouragements

EnrolEnc1. Mon conjoint m'a encouragé à m’inscrire à ce cours en ligne.

EnrolEnc2. Ma famille m'a encouragé à m’inscrire à ce cours en ligne.

EnrolEnc3. Mon employeur m'a encouragé à m’inscrire à ce cours en ligne.

EnrolEnc4. Mes amis m’ont encouragé à m’inscrire à ce cours en ligne.

StudyEnc2. Mon conjoint m’a offert son soutien pour que je fasse des études.

Time-Events

InsuffTime4. Un changement dans mon travail a fait en sorte que je n’ai plus suffisamment de temps pour étudier.

Events1. Un changement à ma situation de travail a fait en sorte qu'il est devenu difficile de suivre ce cours en ligne.

Events2. J’ai été malade pendant ce cours en ligne, de sorte qu’il m’a été difficile de garder un bon rythme.

Events3. Des circonstances personnelles / familiales, qui n’étaient pas là au moment de l'inscription, ont entravé mes études.

Potential Dropout

PotDrop1. *Je suis très déterminé à finir ce cours en ligne.

PotDrop2. Je pense souvent abandonner ce cours en ligne.

PotDrop4. Je suis indécis quant au fait de finir ce cours en ligne.

PotDrop5. Je suis sur le point d’abandonner ce cours en ligne.

PotDrop6. J’ai déjà abandonné ce cours en ligne.

Cost-Benefit

CostBen1. Au fur et à mesure que j’avance dans ce cours en ligne, je pèse continuellement les avantages et les inconvénients des coûts de rester dans le programme.

CostBen2. Comme je continue à m’inscrire à des cours en ligne, je me demande toujours si le coût financier en "vaut la peine" pour continuer.